

Cauchy-Schwarz  $|v \cdot v| \leq \|u\| \|v\|$ . Triangle Inequality  $\|u+v\| \leq \|u\| + \|v\|$ . Distance  $d(u,v) = \|u-v\|$ .  $\cos \theta = \frac{u \cdot v}{\|u\| \|v\|}$ .  $\|u+v\|^2 = \|u\|^2 + \|v\|^2$  iff  $u$  is orthogonal to  $v$ .

$proj_u v = \left(\frac{v \cdot u}{u \cdot u}\right)u = \frac{v \cdot u}{\|u\|^2}u$ . Where  $p$  is a point on the line,  $n_i$  is a normal vector to the line, and  $d$  is a direction vector on the line: Normal Form:

$$\text{line} \rightarrow \begin{cases} n_1 \cdot x = n_1 \cdot p_1 \\ n_2 \cdot x = n_2 \cdot p_2 \end{cases} \text{ plane} \rightarrow n \cdot x = n \cdot p. \text{ General Form: line} \rightarrow \begin{cases} a_1x + b_1y + c_1z = d_1 \\ a_2x + b_2y + c_2z = d_2 \end{cases} \text{ plane} \rightarrow ax + bx + cz = d. \text{ Vector Form: line} \rightarrow x = p + td. \text{ plane} \rightarrow x = p + su + tv.$$

Parametric Form (Just expand the Vector form into three equations. Homogeneous system  $\rightarrow Ax = 0$ . Distance from point  $B = (x_0, y_0, z_0)$  to plain  $ax + by + cz = d$  is  $\frac{|ax_0 + by_0 + cz_0 - d|}{\sqrt{a^2 + b^2 + c^2}}$ . Unique infinite solution(s)  $\rightarrow$  consistent, No solutions  $\rightarrow$  inconsistent. A matrix is in row echelon form if it satisfies the following properties: Any row consisting

entirely of zeros is at the bottom. In each nonzero row, the first nonzero entry is in a column to the left of any leading entries below it. The **rank** of a matrix is the number of nonzero rows in its row echelon form. Rank Theorem # of free variables  $v = n - \text{Rank}(A)$  where  $n$  is the number of variables. reduced row echelon form: 1) It is in row echelon form. 2) The leading entry in each nonzero row is a 1. 3) Each column containing a leading 1 has zeros everywhere else. 2.6: Let  $v_1, v_2, \dots, v_m$  be column vectors in  $\mathbb{R}^n$  and let  $A$  be the  $n \times m$  matrix  $[v_1 \dots v_m]$  with these vectors as its cols. Then  $v_1, \dots, v_m$  are lin. dep. if and only if the homogeneous linear system  $[A]0$  has a nontrivial solution. 2.7: Given  $[v_1 \dots v_m]^T$  then  $v_1, \dots, v_m$  are linearly dependent if and only if  $\text{rank}(A) < m$ . Symmetric  $\rightarrow A = A^T$ . Algebraic Properties of Matrices include: (+, scalar) Commutativity, Associativity, Identity, +inverse, distributivity Transpose Properties Theorem 3.4:  $(A^T)^T = A$ ,  $(A+B)^T = A^T + B^T$ ,  $(kA)^T = k(A^T)$ ,  $(AB)^T = B^T A^T$ ,  $(A^T)^T = (A^T)^T$  Theorem 3.5: If  $A$  is a square matrix, then  $A + A^T$  is a symmetric matrix. For any matrix  $A$ ,  $AA^T$  and  $A^T A$  are symmetric matrices. T 3.6: Inverses of square matrices are unique. T 3.7:  $A$  invertible  $\rightarrow Ax = b$  has a unique solution. T 3.9:  $A$  invertible  $\rightarrow A^{-1}$  invertible.  $(cA)^{-1} = \frac{1}{c}A^{-1}$ ,  $(AB)^{-1} = B^{-1}A^{-1}$ ,  $(A^T)^{-1} = (A^{-1})^T$ .  $(A^n)^{-1} = (A^{-1})^n$ ,  $A^{-n} = (A^{-1})^n$ .  $(A_1 \times \dots \times A_n)^{-1} = A_n^{-1} \times \dots \times A_1^{-1}$ . T 3.10: Let  $E$  be an elementary matrix, then performing that operation on  $A$  is the same as  $EA$ . T 3.11: Each elementary matrix is invertible and its inverse is an elementary matrix of the same type. Def: Let  $A$  be a square matrix. A factorization of  $A = LU$ , where  $L$  is **unit** lower triangular and  $U$  is upper triangular, is called an  $LU$  factorization. Consider  $Ax = b$ , and then  $Ax = LUx = L(Ux) = b$ . Let  $LU = y$ . Now solve  $Ly = b$ , and then  $Ux = y$ . Find  $LU$  factorization: Row reduce to  $ref$  form using elementary (in order top to bottom column by column) row ops of the form  $R_{row} - kR_{col}$ . Then place  $k$  in the identity matrix at row, col. T 3.16: If  $A$  is an invertible matrix that has an  $LU$  factorization, then  $L$  and  $U$  are unique. Def: A subspace of  $\mathbb{R}^n$  is any collection  $S$  of vectors in  $\mathbb{R}^n$  such that (1)  $0 \in S$ , (2) closed under addition and (3) scalar multiplication. T 3.19: For  $v_{i=1, \dots, k} \in \mathbb{R}^n$ ,  $\text{span}(v_1, \dots, v_k)$  is a subspace of  $\mathbb{R}^n$ . Def: row space of  $A$  is the subspace  $\text{row}(A)$  spanned by the rows of  $A$ . Def: col space of  $A$  is the subspace  $\text{col}(A)$  spanned by the cols of  $A$ . T 3.20: Let  $B$  be any matrix that is row equivalent to a matrix  $A$ . Then  $\text{row}(A) = \text{row}(B)$ . (Two matrices are row equivalent iff they can be reduced to the same row echelon form.) T 3.21: Let  $A$  be an  $m \times n$  matrix and let  $N$  be the set of solutions to  $Ax = 0$ . Then  $N$  is a subspace called the null space. Def: A basis for a subspace  $S$  of  $\mathbb{R}^n$  is a set of vectors in  $S$  that (1) spans  $S$  and (2) is Lin. Ind.. To find the  $\text{row}(A)$ ,  $\text{col}(A)$ ,  $\text{null}(A)$ : (1) find  $R = rref(A)$ . (2) Use the nonzero row vectors of  $R$  containing leading 1s to form a basis for  $\text{row}(A)$ . (3) Use the column vectors of  $A$  with leading 1s in  $R$  as a basis for  $\text{col}(A)$ . (4) use  $Rx = 0$  to find the  $\text{null}(A)$ . T 3.23: Any two bases for  $S$  have the same number of vectors. Def:  $\dim(S)$  is the number of vectors in the basis for  $S$ .  $\dim(\text{row}(A)) = \dim(\text{col}(A)) = \text{rank}(A) = \text{rank}(A^T)$ .  $\text{nullity}(A) = \dim(\text{null}(A))$ . Let  $A$  be an  $m \times n$  matrix, then  $\text{rank}(A) + \text{nullity}(A) = n$ . T 3.28:  $A : m \times n$ . (1)  $\text{rank}(A^T A) = \text{rank}(A)$ . (2)  $A^T A$  is invertible iff  $\text{rank}(A) = n$ . Def: Let  $S$  be a subspace of  $\mathbb{R}^n$  and let  $B = \{v_1, \dots, v_k\}$  be a basis for  $S$ . Let  $v \in S$ ,  $v = c_1 v_1 + \dots + c_k v_k$  where  $v_B = [c_1 \dots c_k]^T$  is called the coordinate vector of  $v$  with respect to  $B$ . Def:  $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$  is a linear transformation if  $T(u+v) = T(u) + T(v)$  and  $T(cu) = cT(u)$ .

$[T] = [T(e_1) \dots T(e_n)]$ .  $(S \circ T)(v) = S(T(v)) = [S][T]v$ . Two transformations are considered inverses if  $S \circ T = T \circ S = I_n$ . For these we have  $[T^{-1}] = [T]^{-1}$ . Let  $A$  be an  $n \times n$  matrix. A scalar  $\lambda$  is called an eigenvalue of  $A$  if there is a nonzero vector  $x$  such that  $Ax = \lambda x$ . Such vectors  $e_\lambda$  are called eigenvectors. The collection of all eigenvectors associated with a  $\lambda$  is called the eigenspace denoted  $E_\lambda = \text{span}(\{e_\lambda\})$  or  $E_\lambda = \{t \cdot e_\lambda\}$ . T 4.2: The determinant of a triangular matrix is the product of the entries on its main diagonal. T 4.3: Let  $A$  be an  $n \times n$  matrix. (1) If  $A$  has a zero row (column) then  $\det(A) = 0$ . (2) If  $B$  is obtained by interchanging two rows (or cols) then  $\det(B) = -\det(A)$ . (3) If  $A$  has two identical rows (or cols)  $\det(A) = 0$ . (4) If  $B$  is obtained by multiplying a row of  $A$  by  $k$  then  $\det(B) = k \det(A)$ . (5) If  $A, B, C$  are identical except that the  $i$ th row (column) of  $C$  is the sum of the  $i$ th rows (cols) of  $A$  and  $B$ , then  $\det(C) = \det(A) + \det(B)$ . If  $B$  is obtained by adding a multiple of one row (column) of  $A$  to another row (column) then  $\det(B) = \det(A)$ . T 4.8:  $A, B : n \times n$ . Then  $\det(AB) = \det(A) \det(B)$ . T 4.7:  $A : n \times n$ .  $\det(kA) = k^n \det(A)$ . T 4.9: If  $A$  is invertible,  $\det(A^{-1}) = \frac{1}{\det(A)}$ . T 4.10:  $\det(A) = \det(A^T)$ . T 4.11:  $A : n \times n$  invertible and  $Ax = b \rightarrow x_i = \frac{\det(A_i(b))}{\det(A)}$  where  $A_i(b)$  means replace the  $i$ th column by  $b$ . Def: The adjoint is the transpose of the matrix of cofactors (the  $\det(\text{submatrix})$ ) So  $C_{11} = \det[a_{22} \dots a_{2n}; a_{n2} \dots a_{nn}]$ .  $\det(A - \lambda I) = 0$  (Characteristic Polynomial). To find the eigenvectors find the null space of  $A - \lambda I$  also called the eigenspace  $E_\lambda$ . Find the basis for the space. Define **algebraic multiplicity** to be its multiplicity as a root of the characteristic equation. Define **geometric multiplicity** of an eigenvalue to be  $\dim(E_\lambda)$ . T 4.15 The eigenvalues of a triangular matrix are the entries on its main diagonal. T 4.16 A square matrix  $A$  is invertible iff 0 is not an eigenvalue of  $A$ . T 4.17: Let  $A$  be an  $n \times n$  matrix then:  $A$  is invertible  $\leftrightarrow Ax = b$  has a unique solution  $\leftrightarrow Ax = 0$  only has a trivial solution  $\leftrightarrow rref(A) = I \leftrightarrow A$  is the product of elementary matrices  $\leftrightarrow \text{rank}(A) = n \leftrightarrow \text{nullity}(A) = 0 \leftrightarrow$  the column vectors of  $A$  are Lin. Ind.  $\leftrightarrow$  the column vectors span  $\mathbb{R}^n \leftrightarrow$  the column vectors are a basis for  $\mathbb{R}^n \leftrightarrow \text{rows}(A)$  are Lin. Ind.  $\leftrightarrow \text{rows}(A)$  span  $\mathbb{R}^n \leftrightarrow \text{rows}(A)$  form a basis for  $\mathbb{R}^n \leftrightarrow \det(A) \neq 0 \leftrightarrow 0$  is not an eigenvalue of  $A$ . T 4.18: Given  $A \in M_{n \times n}$  with eigenvalue  $\lambda$  and eigenvector  $x$ , then (a) For any positive integer  $n$ ,  $\lambda^n$  is an eigenvalue of  $A^n$  with corresponding eigenvector  $x$  (b) If  $A$  is invertible then  $1/\lambda$  is an eigenvalue of  $A^{-1}$  with corresponding eigenvector  $x$  (c) For any integer  $n$ ,  $\lambda^n$  is an eigenvalue of  $A^n$  with eigenvector  $x$ . T 4.19:  $A \in M_{n \times n}$  with eigenvectors  $v_1, \dots, v_m$ . If  $x \in \mathbb{R}^n$  that can be expressed as  $x = c_1 v_1 + \dots + c_m v_m$ , then for any integer  $k$ ,  $A^k x = c_1 \lambda_1^k v_1 + \dots + c_m \lambda_m^k v_m$ . 4.4. D:  $A$  is similar to  $B$  if there is an invertible matrix  $P$  such that  $P^{-1}AP = B$  denoted  $A \sim B$ . Note  $P$  is not unique, let  $A \sim I \sim$  is an equivalence relation  $(A \sim A, A \sim B \rightarrow B \sim A, A \sim B$  and  $B \sim C \rightarrow A \sim C)$ . T 4.22: If  $A \sim B$  then (a)  $\det(A) = \det(B)$ , (b)  $A$  is invertible iff  $B$  is invertible, (c)  $\text{rank}(A) = \text{rank}(B)$ , (d)  $A$  and  $B$  have the same characteristic polynomial, (e)  $A$  and  $B$  have the same eigenvalues. D: An  $n \times n$  matrix  $A$  is diagonalizable if there is a diagonal matrix  $D$  such that  $A \sim D$  or  $P^{-1}AP = D$ . T 4.23  $A$  is diagonalizable if and only if  $A$  has  $n$  Lin. Ind. eigenvectors. Where  $P$  is made up of the Lin. Ind. eigenvectors and the entries of  $D$  are made up of the corresponding eigenvalues. T 4.24: If  $\lambda_1, \dots, \lambda_k$  are distinct eigenvalues of  $A$  and  $B_i$  is the basis for the eigenspace  $E_{\lambda_i}$ , then  $B = B_1 \cup \dots \cup B_k$  is Lin. Ind.. T 4.25: If  $A_{n \times n}$  has  $n$  distinct eigenvalues, then  $A$  is diagonalizable. L4.26: If  $A_{n \times n}$ , then for each eigenvalue, the geometric multiplicity  $\leq$  algebraic multiplicity. T 4.17:  $A_{n \times n}$  is diagonalizable  $\leftrightarrow B$  in (T4.24) contains  $n$  vectors. algebraic multiplicity = geometric multiplicity for each eigenvalue. 5.1: D Orthogonal set if  $v_i \cdot v_j = 0 \forall i \neq j$ . T 5.1: If  $\{v_1, \dots, v_k\}$  is an orthogonal set, then the vectors are Lin. Ind.. D: An orthogonal basis for a subspace is also an orthogonal set. T 5.2: Let  $\{v_{i,k}\}$  be an orthogonal basis for  $W$ .  $w \in W \rightarrow w = c_1 v_1 + \dots + c_k v_k$  where  $c_i = (w \cdot v_i) / (v_i \cdot v_i)$  (projection). D: An orthonormal set is an orthogonal set of unit vectors. An orthonormal basis for a subspace  $W$  of  $\mathbb{R}^n$  is a basis of  $W$  that is an orthonormal set. T 5.3: Let  $\{q_{i,k}\}$  be an orthonormal basis for  $W$ . Then  $w \in W \rightarrow w = (w \cdot q_1)q_1 + \dots + (w \cdot q_k)q_k$  is unique. T 5.4: The cols of an  $m \times n$  matrix  $Q$  form an orthonormal set iff  $Q^T Q = I_n$ . D: An  $n \times n$  matrix whose cols form an orthonormal set is called an **orthogonal matrix**  $\rightarrow Q^{-1} = Q^T$ . T 5.6:  $Q$  is orthogonal  $\leftrightarrow \|Qx\| = \|x\| \leftrightarrow Qx \cdot Qy = x \cdot y$ . T 5.7:  $Q$  orthogonal matrix  $\rightarrow$  rows form an orthonormal set. T 5.8: Let  $Q$  be an orthogonal matrix then (a)  $Q^{-1}$  is orthogonal. (b)  $\det(Q) = \pm 1$ . (c) If  $\lambda$  is an eigenvalue of  $Q$  then  $|\lambda| = 1$ . (d) If  $Q_1$  and  $Q_2$  are orthogonal  $n \times n$  matrices, then so is  $Q_1 Q_2$ . D Let  $W$  be a subspace of  $\mathbb{R}^n$ . We say that a vector  $v$  in  $\mathbb{R}^n$  is orthogonal to  $W$  if  $v$  is orthogonal to every vector in  $W$ . The set of all vectors that are orthogonal to  $W$  is called the orthogonal complement of  $W$ , denoted  $W^\perp$ . That is  $W^\perp = \{v \in \mathbb{R}^n : v \cdot w = 0 \text{ for all } w \in W\}$ .

T 5.10:  $(\text{row}(A))^\perp = \text{null}(A)$  and  $(\text{col}(A))^\perp = \text{null}(A^T)$ . D:  $proj_W(v) = proj_{u_1}(v) + \dots + proj_{u_k}(v)$ . Then  $perp_W(v) = v - proj_W(v)$ . T 5.11:  $v = w + w^\perp$  where  $w$  and  $w^\perp$  are unique. T 5.13: If  $W$  is a subspace of  $\mathbb{R}^n$  then  $\dim W + \dim W^\perp = n \rightarrow \text{rank}(A) + \text{nullity}(A) = n$ . T 5.15: Gram-Schmidt process: Let  $\{x_1, \dots, x_n\}$  be a basis for a subspace  $W$  of  $\mathbb{R}^n$  and define the following:  $v_1 = x_1$ ,  $v_k = x_k - \sum_{j=1}^{k-1} ((v_j \cdot x_k) / (v_j \cdot v_j)) v_j$  for each  $1 < i \leq n$ . The set  $\{v_1, \dots, v_n\}$  is an orthogonal basis for  $W$ . D: A square matrix  $A$  is **orthogonally diagonalizable** if there exists an orthogonal matrix  $Q$  and a diagonal matrix  $D$  such that  $Q^T A Q = D$ . T 5.17 If  $A$  is diagonalizable, then  $A$  is symmetric:  $Q^T A Q = D \rightarrow A = Q D Q^T$ ,  $A^T = (Q D Q^T)^T = (Q^T)^T D^T Q^T = Q D Q^T = A$ . T 5.18 If  $A$  is a real symmetric matrix, then the eigenvalues of  $A$  are real. T 5.19: If  $A$  is symmetric, then any two eigenvectors corresponding to distinct eigenvalues of  $A$  are orthogonal. T 5.20 (Spectral Theorem) Let  $A$  be an  $n \times n$  real matrix. Then  $A$  is symmetric if and only if it is orthogonally diagonalizable. (Spectral Decomposition):  $A = Q D Q^T = [q_1 \dots q_n] \lambda_{i=1, \dots, n} Q^T = \lambda_1 q_1 q_1^T + \dots + \lambda_n q_n q_n^T$ . 6.1: A vector space is a field  $(V, +, \cdot)$  (1)+closure, (2)+commutativity (3)+associativity (4) $\exists 0 \in V$  (5)additive inverses  $u + (-u) = 0$  (6)-closure (7)  $c(\vec{u} + \vec{v}) = c\vec{u} + c\vec{v}$  (8)  $(c+d)\vec{u} = c\vec{u} + d\vec{u}$  (9)  $c(d\vec{u}) = (cd)\vec{u}$  (10)  $1u = u$ . D: Vector subspace has the same def= closure under addition and scalar multiplication. 6.2 D: linear dependence: Given  $\{v_{1,k}\}$  then for  $c_1, \dots, c_k$  at least one of which is non-zero  $c_1 v_1 + \dots + c_k v_k = 0 \rightarrow$  lin. dep.. D: A set  $S$  of vectors in a vector space  $V$  is lin. dep. if it contains finitely many lin. dep. vectors. T 6.6:  $[u+v]_B = [u]_B + [v]_B$ ,  $[cu]_B = c[u]_B$ . T 6.7: Let  $B = \{v_{1,n}\}$  be a basis for a vector space  $V$  and let  $u_1, \dots, u_k$  be vectors in  $V$ . Then  $\{u_1, \dots, u_k\}$  is Lin. Ind. in  $V$  if and only if  $\{[u_1]_B, \dots, [u_k]_B\}$  is Lin. Ind. in  $\mathbb{R}^n$ . T 6.10: Let  $V$  be a vector space with  $\dim V = n$ . Then (a) Any Lin. Ind. set in  $V$  contains at most  $n$  vectors. (b) Any spanning set for  $V$  contains at least  $n$  vectors. (c) Any Lin. Ind. set of exactly  $n$  vectors in  $V$  is a basis for  $V$ . (d) Any spanning set for  $V$  consisting of exactly  $n$  vectors is a basis for  $V$ . (e) Any linearly independent set in  $V$  can be extended to a basis for  $V$ . (f) Any spanning set for  $V$  can be reduced to a basis for  $V$ . 6.3: Let  $B = \{u_{1,n}\}$ ,  $C = \{v_{1,n}\}$  be bases for a vector space  $V$ . The  $n \times n$  matrix whose cols are the coordinate vectors  $[u_1]_C, \dots, [u_n]_C$  of vectors in  $B$  with respect to  $C$  is denoted by  $P_{C \leftarrow B}$  and is called the change of basis matrix from  $B$  to  $C$ :  $P_{C \leftarrow B} = [u_1]_C, \dots, [u_n]_C$ . (a)  $P_{C \leftarrow B}[x]_B = [x]_C$  in  $V$ . (b)  $P_{C \leftarrow B}$  is the unique matrix  $P$  with the property that  $P[x]_B = [x]_C$  for all  $x \in V$ . (c)  $P_{C \leftarrow B}$  is invertible and  $(P_{C \leftarrow B})^{-1} = P_{B \leftarrow C}$ .

Gauss-Jordan Method: Let  $C = P_{E \leftarrow C}$ , and  $B = P_{E \leftarrow B}$ . Then  $[CIB] \rightarrow [IP_{C \leftarrow B}]$ . D: Let  $T : V \rightarrow W$  be a linear transformation.  $\ker(T) = \{v \in V : T(v) = 0\}$ ,  $\text{range}(T) = \{T(v) : v \in V\}$ . T 6.18  $\ker(T)$  is a subspace,  $\text{range}(T)$  is a subspace. D:  $\text{rank}(T) = \dim(\text{range}(T))$ ,  $\text{nullity}(T) = \dim(\ker(T))$ . T 6.19:  $\text{rank}(T) + \text{nullity}(T) = \dim(V)$ . D: A linear transformation  $T : V \rightarrow W$  is called **1-to-1** if  $T$  maps distinct vectors in  $V$  to distinct vectors in  $W$ . If the  $\text{range}(T) = W$ , then  $T$  is called **onto**.  $T$  is 1-to-1 if  $\forall u, v$   $u \neq v \Rightarrow T(u) \neq T(v)$  or  $T(u) = T(v) \Rightarrow u = v$ .  $T$  is **onto** if  $\forall w \in W, \exists v \in V$  s.t.  $w = T(v)$ . T 6.20: A linear transformation  $T : V \rightarrow W$  is 1-to-1 iff  $\ker(T) = \{0\}$ . T 6.21: Let  $\dim(V) = \dim(W) = n$ . Then a lin. trans.  $T : V \rightarrow W$  is 1-to-1 iff it is onto. Let  $T : V \rightarrow W$  be a 1-to-1 linear transformation, if  $S$  is a set of Lin. Ind. vectors in  $V$ , then  $T(S)$  is a set of Lin. Ind. vectors in  $W$ . (do it with  $\dim V = \dim W = n$ , and  $|S| = n$ , you get a basis to a basis.) T 6.24: A Lin. Trans. is invertible iff it is 1-to-1 and onto. D: A Lin Trans. is called an **isomorphism** if it is 1-to-1 and onto. If  $\exists T : V \rightarrow W$ , 1-to-1, onto, then  $V$  is isomorphic to  $W$  denoted  $V \cong W$ . T 6.25  $V$  is isomorphic to  $W$  iff  $\dim V = \dim W$ .